Personalized Content-based Recommender System: End-to-end Deep Learning Approach

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Collaborative filtering is one of the leading algorithms which are used to suggest personalized products (ads, movies, book, etc.) to clients (Chen et al., 2016; Hernando, Bobadilla, & Ortega, 2016). There are many disadvantages using collaborative filtering for genuinely personalized suggestions. Its underlying assumption that data collected from preferences of others can shape decision about a preference of a specific client is not always valid and not necessarily accurate. In addition, collaborative filtering has an inherent problem with new products that people have not labeled yet (cold start items) (Wei et al., 2017).

This article suggests replacing collaborative filtering with end-to-end deep learning for truly personalized content based recommender system. This approach will be demonstrated with personalized movies suggestions, but it applies to all kinds of products.

The input (X) of the deep neural network (DNN) is a concise description (text) of movies extracted from the web. The output (Y) of the DNN is client's preference (a simplified example of 2 classes: 1 for like & 0 for dislike).

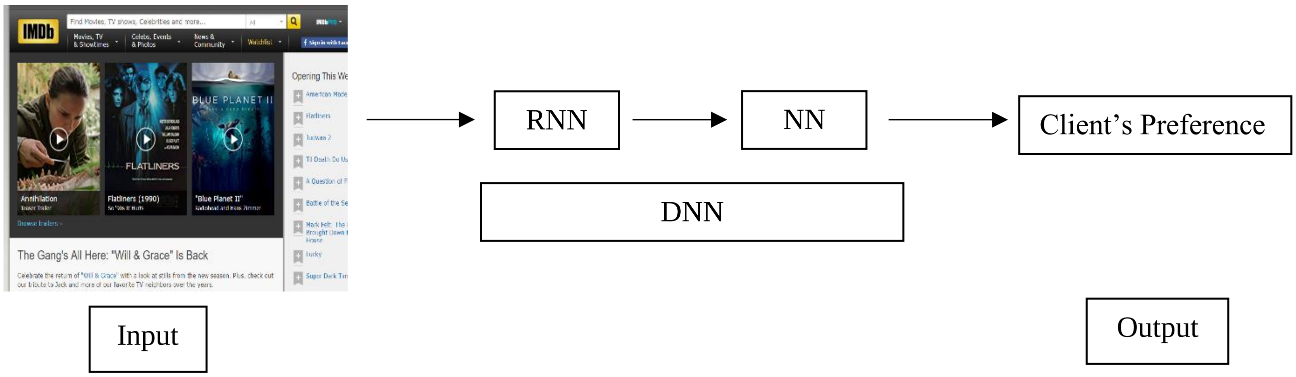
Practically the trained DNN would be divided into two main functional parts. The first part of the DNN (first hidden layers) should learn to detect main themes or features of movies extracted from the web and should be designed as a recurrent neural network (RNN) (Sutskever,

Martens, & Hinton, 2011). The second part of the DNN stacked on the previous hidden layers is practically a personalized neural network (with a specific personalized set of weights) that has been continuously developed and personalized for each client according to his or her preferences and reflects client's personal taste.

In order to make this approach of end-to-end deep learning for recommender system effective, ***transfer learning*** should be implemented. The weights of the first hidden layers (RNN) can be used and adjusted over all clients. The task of the first layers is to detect themes or features of movies (not personalized information). The second part of the DNN stacked on the RNN should be completely personalized for each client, with a specific personalized set of weights that have been continuously developed and personalized for each particular client according to his or her preferences.

This approach has the potential to move recommender systems forward to a new level of personalized recommendations and does not have problems with new products that people have not labeled yet. The weights of the personalized neural network can be initialized by a series of questions introduced to the client, and are continuously fine-tuned directly by client's preferences and not influenced by others' preferences.

Drawing of the System - General View



References

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